Abbasi, R, Kashif Bashir, A, Jianwen, C, Mateen, A, Piran, J, Amin, F and Luo, B (2021) Author classification using transfer learning and predicting stars in co-author networks. Software - Practice and Experience, 51 (3). pp. 645-669. ISSN 0038-0644

Author Classification using Transfer Learning and Predicting Stars in Co-Author Networks

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Abstract

The vast amount of data is key challenge to mine a new scholar that is plausible to be star in the upcoming period. The enormous amount of unstructured data raise every year is infeasible for traditional learning; consequently, we need a high quality of preprocessing technique to expand the performance of traditional learning. We have persuaded a novel approach, Authors classification algorithm using Transfer Learning *(ACTL)* to learn new task on target area to mine the external knowledge from the source domain. Comprehensive experimental outcomes on real-world networks showed that *(ACTL)*, Node-based Influence Predicting Stars *(NICPS)*, Corresponding Authors Mutual Influence based on Predicting Stars *(CAMIPS)* and Specific Topic Domain-based Predicting Stars *(STDPS)* enhanced the node classification accuracy as well as predicting rising stars to compared with contemporary baseline methods.

KEYWORDS:
Social network; Transfer learning; Prediction; Author classification

1 | INTRODUCTION

Academic Social Networks *(ASN)* based on co-author and citation oriented relationships between authors, research articles, and co-authors contribution in different research article[1]. *ASN* task as a professional finding[2], professional interest finding[3], tag disambiguation[2,4 5], citation recommendations[6], and rising star finding. This work reveals the predicting rising stars to predict new researchers with skills to become an expert in future while the scholars with a low profile but having a potential to be on top in future are referred as rising stars[7]. Previously, when a new researcher was contributing with a senior researcher on the high-rank publication venue had more chances to be a star in the future. *ASN*[8 9] based on co-authorship, co-reference relationship and social tagging[10]. Microsoft Academic Search and Arnetminer are online services which store the information of scholars such as predicting experts[11] and research collaboration[12,13,14,15].

Li et al.[7] focused the mutual influence and static score of venues; moreover, author[16] suggested the dynamic author's research profiles by grouping the authors inversely by using non-supervised learning approaches. PubRank[7] algorithm upgraded by StarRank[1] method which considered the author contributions based on mutual influence. The objective is to find the rising stars which result "Weather a scholar to be rising star or not in future"[13,14]. PageRank[17] is a key feature finding technique from the graph, extracting the keywords, and key phrases from documents which further attained by TextRank[18]. PubRank[7] proposed for academic social networks for predicting the rising stars to consider the mutual influence and previous record of scholar publications on different venue; moreover, StarRank[1] based on PubRank to magnify the co-author contribution and mutual influence from researchers networks. Rising stars prediction which is a small work has been carried out in academic social networks while the main idea is that whether a junior researcher work with expert researcher having chances to be expert in future.

1.1 | Key Challenges and Motivations

The key challenge is to mine the future predicting stars from two or more different networks who will be a predicting star in forthcoming. Normally the social networks are designed for a particular purpose and every network have its own entities representing by its nodes and related links which shows the different relationship between the nodes. Apart from the different network's relationship, for example: in a citation relationship of two diverse networks both have their own features for nodes. it is unable to get accurate classification through traditional machine learning. The most significant to compute the influence of one researcher to other researchers as well as the first researcher is generally pondered to be a top contributor as compare with second and so on. Moreover, PubRank method[7] used the non-dynamic ranking method which does not deliver the newest ranking list of publication venues. StarRank[1] calculated the mutual influence of author contribution which does not consider the corresponding author weight, besides didn't determine the track record of author research area with respect of author publication venues.

The massive amount of unstructured data is increasing on a different domain on the web is a key challenge due to infeasible of traditional learning as a result, we need a high quality of classification approach to expand the performance of machine learning techniques to predict future rising stars[19,20,21,22].

Two networks are frequently exchanged some similar features; however, the information of nodes features is not exchangeable. For example, two citation networks, the *CiteSeer* network having *3,327* nodes, while *2,708* nodes in *Cora* network. Both networks have no similarities in nodes or edge; however, both the networks exchange some common sub-graph that represents some frequent structures patterns with prominent similarities in the cross-network. It's very problematic to classify unlabeled nodes to train a virtuous classifier due to the deficiency of labeled node; moreover, mutually classification can give a higher classification consequence compare with traditional-leaning techniques[23,24]. A learning framework required well-connected information to achieve the learning objective for an authorąŕs classification. In cross authors networks, a node exchange its common feature to achieve the accurate performance for authors classification; therefore, it is required to have the same structure in networks and generalize sub-graph for transferring the related structural features which frequently occur between two networks to improve the author classification in target network.

1.2 | Contribution

The aim of transfer learning is to learn a new task in the target area to mine external knowledge from source area[25]. We proposed a new method for author classification via cross-network transfer learning. Our main idea is to explore the similar signature graphs patterns between the networks i.e. source network and the target network, which bring the improvement in author classification of the target network. (1) In the first phase, we have used state of the art method for training and validation from the source domain, Author based Classification algorithm using Transfer Learning *(*ACTL).

(2) In the second phase, there are different kinds of challenges in social influences analysis. The first challenge is that how to control the network structure to computes the social influence. The influence between each other does not only depend upon their own topics but also have a social relationship with other authors. The main task is to find a unique approach to utilize both the local attributes i.e. topic distribution and the global structure of network information for the analysis of social influence. How to compute social influence score, we can discriminate with

diverse angles, and how to discover the strength of social influence with respect of fair contribution within a specific domain. Consequently, we need to quantify the mutual influence score to predict the precise future rising stars.

We proposed a new algorithm, Corresponding Author Mutual Influence *(CAMI)*, Node base Influence Score *(NIC)* to compute mutual influence score auxiliary, predict expert finding using *NIC* based Predicting Stars *(NICPS)*, *CAMI* based Predicting Stars finding *(CAMIPS)*, Specific Topic domain based Predicting Stars finding *(STDPS)*.

Prearranged our remainder part as follows. Section 1, described the introduction. Section 2, we have discussed related work, and section 3, described the proposed algorithms. Section 3.1, and subsection defined different node-weighting schemes, section 3.2, and subsections defined the predicting stars finding by using different schemes. Performance evaluation result described in section 4 and the conclusion finalized in Section 5.

2 | RELATED WORK

In the field of social network and data mining, one of the important learning tasks is the author classification from different networks. For instance, we have a number of nodes and some of them are labeled while some are unlabeled. The combination of structural features and content of the labeled nodes to classify the unlabeled node [26,27]. The collective classification achieves higher classification accuracy compared with the individual classification methods shown in the previous techniques [28,29]. A collective classification method to decrease the learning and inference changes within the domains whereas the same set of nodes are connected by multiple networks [30]. Transfer learning is efficaciously useful in many application area of machine learning like, image classification [31], text classification [27], and human activity classification [28,29,30].

2.1 | Transfer Learning

The data mining and machine learning have many applications where data is extracted from one domain to visualize into other domain. However, in traditional learning, the source domain (training data) and the target domain (testing data) have the same data distribution and feature space beside in case of difference in source and target domain the predictive learner result can be decline to predict the rising stars [32,14]. The main inspiration of transfer learning is to improve the performance of learners to the optimum level of target data and get the information from the relevant domain where the labeled data is very small in numbers [33]. Traditional machine learning result is a decline for the reason of the difference in domain data while Transfer leaning, the core intention is to apply knowledge and extract the key information from other domain.

In the first class, instance transfer method is used to transfer an information [34,35] in which the instance weighting in the target domain, the most parts of instances are reused for learning and assign larger weights in both the source and target domain [34]. The common parameter method is lying in the second category of transferring the information where the source and target learning task share the same parameter [36,37,38]. The lack of a labeled node is the main concern for the classifier to predict the unlabeled node. In many social networks, the content feature is not allied with the node; however, they are the mutual influence and share common dependency [23,43,44]. Mutually classification can give higher classification outcome to compare with traditional-leaning method [45,46]. Mutual social influence is an important factor to compute the influence between two nodes. The graphical model generally we can use to predict the social connections for training and prediction of the corresponding relationship attributes to increase the labels of conditional probability. Many graphical models are extensively used to designate the dependencies between the data like Restricted Boltzmann Machine [47] factor graph [48].

The frequent sub-graph mining [49,50] and influence pattern finding in a large network to transfer those sub-graph structures whose threshold is above the minimum support in the graph data-set [51]. The high-frequency pattern plays a very important role in graph database indexing [46]. For finding the recurrent subgraph pattern, an adjacency matrix is used to present the graph in AGM method [49]. GSpan [50] method to avoid the graph isomorphism in which the frequently connected subgraph has effectively adopted a new lexicographic order to map each graph by using depth-first search (DFS). We proposed to find a similar subgraph from both the networks i.e. source and target networks to make it possible to transfer the information between two networks to compute the author influence/ author weight and future predicting stars.

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3 | AUTHOR BASED CLASSIFICATION ALGORITHM USING TRANSFER LEARNING (ACTL)

To assist the target learning task is to find transferable knowledge across both the networks which are our main focus in the transfer learning scheme. Nodes have the same labels, which have the same structure and either they are connected or tends to be connected closely. Consequently, explore the common structure pattern which can help in author classification in the targeted network[36,38]. For author classification, our *(*ACTL) technique is basically comprised of three steps.
Step 1:- Build structure features from both the networks.
Step 2:- Reconstructed the features of the target network from our explored similar signature subgraph by source and target network.
Step 3:- For learning a classifier together in a target network to classifying and reconstruct the feature of author.

A network comprised of a set of nodes and edges, besides each node will describe two types of feature, Content features define the features of the node while the structure feature defines the node with respect to neighborhood structure information[39]. In this work, we defined the structure information of the node based on the author subgraph. First, we explore the major structure patterns of the neighborhood node. Suppose the label of node depend upon its neighborhood structure which is contained by the depth of s for any node v For example, a node v consider as a root node in the network, using a breadth-first search *(BFS)*[47] crawl to the neighborhood structure of the node with the depth of s. Suppose the *DBLP* network, we build neighborhood structures for node A. We propose a way to represent a uniform level of neighborhood structures based on the similarity of two sub-graphs; furthermore, define by a mapping function $M : (n, s) \longrightarrow n$, describe the structure of node n to make a vector within the depth s of s-neighborhood structures. We able to establish a set of subgraph just in case s-neighborhood structure is organized by means of subgraphs to signify the neighborhood structure. Let we represent the whole space $A = (a_1, a2, ..., a_k)$, then based on subgraph we can built a mapping function of M. Consequently, The formed values from subgraph-based feature vector $v_1, ..., v_k$ where subgraph based a_i will be equivalent feature value of v_i.

A graph $D = (N, E)$ and the node $(n \epsilon N)$, scan recursively from root node to all neighbor nodes till the depth of node s,as well as s-neighborhood structures d_n is subtree of node n which comprise of all inventive link and visited nodes. $d = (N_d, E_d)$, where, d is subgraph of D,
$\forall n \epsilon N_d, f(n) \epsilon D;$
$\forall (t, n) \epsilon E_d, (f(t), f(n)) \epsilon E.$

The graph $D = (N, E)$, subgraph bases A=$\{a_1, a_2, ..., a_k\}$ and $\{v_1, ..., v_k\}$ is the group of value where every V_i value is relates to a_i of subgraph A=$\{a_1, a_2, ..., a_k\}$; moreover, the graph D as well as author subgraph bases A is exclusively define $D^{'}$.

Discover the subgraph bases A and its corresponding values to compute from graph D by means of s- neighborhood structures.

$$A = \{a_1, a_2, ..., a_k\} = Exclusive\{d_1, d_2, ..., d_k\} \tag{1}$$

The association between the author subgraph is establish using s-neighborhood structures $A = a_1, a_2, ..., a_k$, in addition to compute the probability value $prb(d|a_i)$, the probability value $prb(d|a_i)$ will be large in case the structure of g to be expected the subgraph base a_i otherwise, the probability value $prb(d|a_i)$ will be near to zero.

$$w = \{v_1, v_1, ..., v_k\} = prb(d|a_1), \{prb(d|a_2), ..., prb(d|a_k)\} \tag{2}$$

$prb(d|a_i)$ the subgraph base of $a_i \epsilon A$ with respect the value of v_i to d. We describe the mutual subgraph between graph D_1 and D_2, besides the graph $D(N, E)$, assume that $|N|$ and $|E|$ represent the sum of nodes and edges. We assume, $|D|$ represent the total sum of nodes and edges of $|D|$ where $D = |N| + |E|$. Compute the probability $prb(d|a_i)$ as follows,

$$prb(d|a_i) = \frac{|Mmutal(d, a_i)|}{Mx(|d|, |a_i)|} \tag{3}$$

The $prb(d|a_i)$ will be larger if more mutual structures of d with a_i, while the $prb(d|a_i)$ will be near to *0* in case small mutual structures of d with a_i. The probability $prb(d|a_i)$ for a known graph d as well as subgraph of a_i has following features.

$0 < prb(d|a_i) \leq 1;$
$prb(d|a_i) = 1 \longleftrightarrow d$ and a_i are Isomorphic, if d_1, d_2 are isomorphic then $prb(d_1|a_i) = prb(d_2|a_i)$

Extract the useful feature from source to the target network and mine the specifiable patterns from D_s to D_t. Even if the network we have an appropriate domain but it's can be some distinct feature in their node. We have to define an optimal set of mutual subgraph $A^*_{(k)}$ to capture mutual pattern between D_s and D_t.

Algorithm 1 Constructing author Subgraph based Mutual Structure Features (ASMSF)

Input: A network $D = (N, E)$,
Output: author subgraph A , and author subgraph based description for all node $n\epsilon N$.
Step 1: Gather all s-neighborhood structures from network D;
Step 2: Make subgraph bases A by means of s-neighborhood structures;
Step 3: **for** for every node $N\epsilon n$ **do**
Step 4: Gather s-neighborhood structure of node d to n;
Step 5: Calculate $prb(d|a_i)$ using equation 3 for every node $a_i\epsilon A$;
Step 6: Obtained author subgraph based description $n = prb(d|a_1)$,..., $prb(d|a_k)$
Step 6: **End for**.

The A_s and A_t describe as subgraph which based on source network and target network D_s, D_t; consequently, find an optimum level set of mutual subgraph $A^*_{(k)}$ which can be select as whole set of A_s union A_t to signify the source and target networks[40].

$$A^*_{(k)} = arg_{A_{(k)}} max \prod_{n\epsilon D_t} prb(d_n|A_{(k)}) \prod_{n\epsilon D_s} prb(d_n|A_{(k)}) \tag{4}$$

$$\begin{aligned} A^*_{(k)} = arg_{A_{(k)}} max & \prod_{n\epsilon D_t} \prod_{a_i\epsilon A_{(k)}} prb(d_n|a_{(i)}) \\ & \prod_{n\epsilon D_s} \prod_{a_i\epsilon A_{(k)}} prb(d_n|a_{(i)}) \end{aligned} \tag{5}$$

The D_s and D_t are source and target network are signified in mutual subgraph to collect unique neighborhood structure[41,42]. We describe

$$F = \prod_{a_i\epsilon A_{(k)}} \{ \prod_{n\epsilon D_t} prb(d_n|a_{(i)}) \prod_{n\epsilon D_s} prb(d_n|a_{(i)}) \} \tag{6}$$

using in log form,

$$logF = \sum_{a_i\epsilon A_{(k)}} log\{ \prod_{n\epsilon D_t} prb(d_n|a_{(i)}) \prod_{n\epsilon D_s} prb(d_n|a_{(i)}) \}, \tag{7}$$

for optimum description to rewrite the Eq.(5) as

$$A^*_{(k)} = arg_{A_{(k)}} max \quad logF. \tag{8}$$

Here, to select the optimum set of $a_i^{'}$ which can be maximize the addition of $log\{\prod_{n\epsilon D_t} prb(d_n|a_{(i)}) \prod_{n\epsilon D_s} prb(d_n|a_{(i)})\}$.
As $0 < prb(d_n|a_{(i)}) \leq 1$

$$log\{ \prod_{n\epsilon D_t} prb(d_n|a_{(i)}) \prod_{n\epsilon D_s} prb(d_n|a_{(i)}) \} < 0. \tag{9}$$

for optimum function to rewrite as

$$A^*_{(k)} = arg_{A_k} min \sum_{a_i \epsilon A_{(k)}} \{-log\{\prod_{n \epsilon D_t} prb(d_n|a_{(i)}) \prod_{n \epsilon D_s} prb(d_n|a_{(i)})\}\}. \tag{10}$$

The source and target D_s and D_t networks used to calculate $prb(d_n|a_{(i)})$ for every node; moreover, to select the set of A^*_k with lowermost value as $-log\{\prod_{n\epsilon D_t} prb(d_n|a_{(i)}) \prod_{n\epsilon D_s} prb(d_n|a_{(i)})$.

Here, we will simplify the classification of the target network to construct a precise classifier on the bases of mutual simplifying author subgraph. Every node of the author graph is not independent while also associated with each other and mutually influence to a connected label of adjacency nodes. Mutual influence classification gives an accurate result and expressively improves the performance of classification as compared with traditional classification method that distinctly classifies the node.[25,37].

We consider three form of feature for every node n and D_t. (1) The attribute value of node n is allied with its modified features of m_n. (2) Compute the n' unique feature representation x_n and gather n' s-neighborhood structure of d_n for specified node n based on mutual subgraph $A^*_{(k)} = \{a_1, a_2, ..., a_k\}$
$m_n = \{v_1, v_2, ..., v_k\}$,
$= \{prb(d_n|a_1), prb(d_n|a_1), ..., prb(d_n|a_k)\}$

x_n is new feature description on node n is used while the target network has unique feature for every node $m_{new} = (m, x)$.

(3) The aggregation function is used to analyze the relational feature for every node and gather the statistical data of the node labels from its adjacent node of n; moreover, any changes on node label will be effected continuously to relational features. The detailed process of author classification using transfer learning describes in algorithm 2.

Algorithm 2 Author based Classification using Transfer Learning *(ACTL)*

Input: Source author network $D_s = \{N_s, E_s\}$, target author network $D_t = \{N^l_t, N^u_t, E_t\}$ and classifier *f*,
Output: The unlabeled node labels in, $N^u_t \epsilon D_t$.
Step 1: Gather s-neighborhood structures from D_s and D_t;
Step 2: Generate author subgraph bases for D_s and D_t;
Step 3: Mutual author subgraph bases learning between D_s and D_t;
Step 4: Mutual author subgraph used to re-generate the structure feature of D_t;
Step 5: For every node n, unique feature are $M_{new} = (M, x)$;
Step 6: for every N^i_t node in D_t **do**
Step 7: Discovered node in its adjacent nodes to calculate relational feature;
Step 8: Unlabeled node $u^i_r \longleftarrow f(n^i_t)$ to predict the label;
Step 9: End for
Step 10: While $u^{i'}_t$ the repetitions number will be within the threshold value **do**
Step 11: The node in D_t to produce ordering ∂;
Step 12: for $N^i_t \epsilon \partial$ every node **do**
Step 13: Predictions of recent label of its adjacent node to calculate relational feature;
Step 14: Unlabeled node $u^i_t \longleftarrow f(n^i_t)$ to predict the label;
Step 15: end for
Step 16: end while
Step 17: N^u_t assign to label prediction.

3.1 | Node-weighting schemes

Ranking problems in network structure by using the PageRank algorithm to calculate the weighting score of authors. Given a set $\{A_1, ..., A_n\}$ represents the number of n authors. Calculating the different mutual influence between the authors to calculate the ranking score called the rising star score. For mutual influence among the authors, we use $n \times n$ matrix having set $W = \{W_1, ..., W_n\}$, in set W each value represent the influence between two authors. For instance, W_{ij} represents the mutual influence of author A_i over author A_j. Following is the ranking function to represent the ranking score of n authors.

$$H(A_i) = \frac{1-d}{n} + d * \sum_{j=1}^{|a|} \frac{(A_i, A_j)}{\sum_{k=1}^{|a|}(A_k, A_j)} * H(A_j) \tag{11}$$

d is damping factor, (A_i, A_j) is author influence weight to calculate the rank of authors. For finding rising stars score of an author A_i, we proposed the following main features that are co-authors, corresponding author mutual influence *(CAMI)*, co-author's citations based mutual influence, co-author's venues based mutual influence, co-author's paper-based mutual influence, and co-author's domain and subtopic domain based influence score.

3.1.1 | Author Influence

The impact of expert researcher contribution with the new/junior researches is said to be an authors influence. For instance, if a new researcher has started his research with expert author evidently new researcher will get more expertise and more author's influence on those researchers they are presently working with low research profile.

Definition.1 The online social web, the graph $D = (N, E)$, respective user is signified by node N while the mutual influence of the corresponding relationship between two nodes is signified as E. To each node $(n_i \varepsilon N)$, where, $i = \{1, 2, ..., n\}$
B_i attributes of user i
$B_i = (b_i^1, b_i^2, ..., b_i^m)$.
Total number of attribute is m and user i, where $j = (1, 2, ..., m)$
W_{ij} is mutual influence amid two nodes.

3.1.2 | Corresponding-Author Mutual Influence (CAMI)

We proposed corresponding authors contribution is based upon mutual influence magnified by co-author contribution and based upon the s index[7].

If a junior researcher collaborates with senior researchers, then they can gain more score and prominent in future Li et al.[7].

$$influnce(Ca_1, Ca_2) = \frac{(Ca_1, Ca_2)}{Pa_2} \tag{12}$$

Total publication of author Ca_2 is Pa_2 where, ca_1, and ca_2 are two co-author.

Presume 5 authors are appearing, the first author in name sequence has more contribution comparatively with the last author because the main theme is when a junior author works with experienced researcher has bright chances to become expert in the future on the another hand last researcher weight will be minimum in that paper author list; however, the last author more or equally contributed with the first author if the last author is the corresponding author.

TABLE 1 Corresponding-authors mutual influence

Authors	Authors order in paper
L	1(1), 2(1), 3(1), 4(1)
M	1(4), 2(4), 3(4), 4(4)
N	1(2), 2(2), 3(3), 4(3)
p	1(3), 2(3), 3(2), 4(2)

For example, all four authors are new researcher, author L and P are corresponding-authors and author L and M are co-author in four paper while author N with P and L with M are contributing with each other in two paper shown in Table 1.

$$\begin{aligned} AS(H_L, H_M) &= \frac{(\sum AS_L + \sum AS_M)}{\sum PAS_M} \\ &= \frac{(1+1)+(1+0.5)}{1+0.5+0.5+1} = 1.05 \end{aligned} \tag{13}$$

$AS(H_M, H_L) = \frac{(\sum AS_M + \sum AS_L)}{\sum PAS_L} = \frac{(1+0.5)+(1+1)}{1+0.5+1+1} = 1$

$AS(H_N, H_P) = \frac{(\sum AS_N + \sum AS_P)}{\sum PAS_P} = \frac{(0.5+0.5)+(1+1)}{0.5+1+0.33+1} = 1.06$

$AS(H_P, H_N) = \frac{(\sum AS_P + \sum AS_N)}{\sum PAS_N} = \frac{(1+1)+(0.5+0.5)}{0.5+0.5+1+0.2} = 1.36$

L and N are two co-authors in a paper, AS_L is author influence score of author L; moreover, PAS_N is individual weight of author *N*. Author P is the corresponding author with N and cooperate in two papers. Author N naming place is second in both two papers while corresponding author P naming place is third in both two papers but his contribution score is higher than N and he influences more than N even his naming position in that paper is third but always influence weight will be equal with the first author in naming sequence. Earlier schemes, all authors gave same weight or assign weight on the base of naming sequence *1, 2, 3* like first author's contribution is more than the second author and the second author's contribution is more than third author and so on.

3.1.3 | Venue eminence

Chronological aspect of an article that is published for a long time ago which get positive chronological association, formulated as[10] while entropy specify the rank of venues and provide an active score[1]; moreover, imperative venues rank have lower entropy and high entropy scores on an inferior rank of those venues.

$$TRW_{(H_i)} = \frac{\sum d(H_i)}{\sum Y_{(d)}} \tag{14}$$

$$Entropy(v) = -\sum_{k=1}^{m} W_k log_2(W_k) \tag{15}$$

$$\lambda(H_i) = \frac{1}{|p|} * \sum_{i=1}^{1} \frac{1}{\alpha^{Entropy(v)}} \tag{16}$$

$TRW(H_i)$ is weight of author H_i and $\sum Y_{(d)}$ is age for publication article, $\lambda(H_i)$ is publication score, value of α is $(0 < \alpha < 1)$

$$\begin{aligned} &CAMI(H_i) \\ &= \frac{1-d}{n} + d * \sum_{j=1}^{|a|} \frac{w(H_j, H_i) * \lambda(H_i) * CAMI(H_j)}{\sum_{k=1}^{|a|} w(H_k, H_j) * \lambda(H_k)} \end{aligned} \tag{17}$$

$w(H_j, H_i)$ is influence to other researcher, n is number of all authors, $\lambda(H_i)$ is publication eminence for author $H_{(i)}$.

3.2 | Predicting stars schemes

3.2.1 | *CAMI* based predicting stars finding *(CAMIPS)*

PubRank[7] proposed from educational social networks to predict rising stars. Here, we have used author influence score as a substitute for static contribution score to identify the future stars.

$$\begin{aligned} &CAMI(Ht) \\ &= \frac{1-d}{n} + d * \sum_{j=1}^{|a|} \frac{w(\mu^d_{Hs}, \mu^d_{Ht}) * \lambda(H_i) * CAMI(H_j)}{\sum_{k=1}^{|a|} w(\mu^d_{Hk}, \mu^d_{Hs}) * \lambda(H_k)} \end{aligned} \tag{18}$$

Algorithm 3 Corresponding-Author Mutual Influence *(CAMI)*

Input: Input authors data
Output: Authors ranking score
Step 1: Construct ca_2, pa_2 value for each author from author network further using Eq. 12 to reckon *ACMI* of all author in succession order.
Step 2: Compute *entropy(v)* by employing Eq. 15
Step 3: Discover the venue importance by using Eq. 16
Step 4: Calculate authors rank using Eq. 4

n is number of whole authors, d is damping factor, value of d=*0.5*, $\lambda(H_i)$ is publication reputation for author Ht.

Algorithm 4 *CAMI* based Predicting Stars finding *(CAMIPS)*

Input: authors influence score, Author network
Output: Authors expert finding
Step 1: Compute *entropy(v)* by employing Eq. 15
Step 2: Discover venue importance by using Eq. 16
Step 3: Work out author influence score by means of Eq. 13
Step 4: Compute authors rank using Eq. 17
Step 5: Compute authors rank using Eq. 18

3.2.2 | Node based Influence score *(NIC)*

There are different influence scores on different nodes in vast social networks. Let, node *'A'* has a strong influence on node *'B'* in one case, while in other case nodes *'B'* has a strong influence over node *'A'*. The effect of social influence may differ from different angles; for instance, in a research community these types of influences are the collaboration and citations influence of the researchers are being strong or weak on each other's[47,48]. For rising stars prediction a small work has been carried out in social networks. Several researchers are collaborating with each other and influenced other researchers in the innumerable cause. The specific topic based social influence identifications using factor graph[52,53], the different domains are interrelated on the basis of diverse social influence weight, for example, data mining domain, A has high influence on B but in image processing, B has high influence on A, consequently this is very important to know about social influence to segregate with respect to different characteristics. To control the similarity at the topic level for social influence identification is our key attention which is based on the theory of factor graph[52], in which the observation data are cohesive on local attributes. The sum-product algorithm is a wait to arrive all the message of the node, so in that case, the algorithm will run in a sequential mode with high complexity. We have adopted an affinity propagation algorithm instead of the factor graph to compute the social influence of the author form two different co-author networks, more detailed presentation is[47,48,54].

$$r_{ij}^d = b_{ij}^d - \max_{k \in AD(j)} \{b_{ik}^d + a_{ik}^d\} \tag{19}$$

$$a_{jj}^d = \max_{k \in AD(j)} \min\{r_{kj}^d, 0\} \tag{20}$$

$$\begin{aligned} a_{ij}^d = \min(\max\{r_{jj}^d, 0\}, -\min\{r_{jj}^d, 0\} - \max_{k \in AD(j)} \\ \setminus\{i\} \min\{r_{kj}^d, 0\}), i \in AD(j) \end{aligned} \tag{21}$$

where $AD(j)$ is adjacent node of j, d is specific domain, b_{ij}^d is logarithm normalized function, r_{ij}^d refer the influence weight from i to j and a_{ij}^d refer the influence weight from j to i.

$$b_{ij}^d = \log \frac{g(v_i, \mathbf{y}_i, d)|_{y_i^d=j}}{\sum_{k \in AD(i) \cup \{i\}} g(v_i, \mathbf{y}_i, d)|_{y_i^d=k}} \tag{22}$$

$$\mu_{st}^d = \frac{1}{1 + e^{-(r_{ts}^d + a_{ts}^d)}} \tag{23}$$

a and r are variable, v_i and v_j are node, while the social influence score based on both variables, μ_{st}^d is social influence of one node to other on the basis of different domain. The social network is a large network that has millions of users connected with each other. Algorithm. 5 node based influence score *(NIC)* obtained μ_{st}^d from large authors network to identify the specific domain based predicting stars.

Algorithm 5 Node base Influence score *(NIC)*

Input: Input authors data $G = (V, E)$
Output: Authors domain based influence graph
Step 1: compute feature function $g(v_i, y_i, d)$
Step 2: Compute b_{ij}^d using Eq. 22
Step 3: Set value $r_{ij}^d \longleftarrow 0$
Step 4: Outer loop
Step 5: loop: author topic pair (e_{ij}, d) **do**
Step 6: calculate r_{ij}^d by using Eq. 19
Step 7: end loop
Step 8: loop: calculate (v_j, d) **do**
Step 9: update a_{jj}^d using to Eq. 20
Step 10: end loop
Step 11: loop (e_{ij}, d)
Step 12: Compute a_{ij}^d using Eq. 21
Step 13: end loop
Step 14: outer loop end
Step 15: loop:node v_t
Step 16: loop: $AD_s \in AD(t) \cup t$
Step 17: compute μ_{st}^d Eq. 23
Step 18: end inner loop
Step 19: end outer loop

3.2.3 | *NIC* based Predicting Stars finding *(NICPS)*

Above algorithm, 3 using PageRank [17] algorithm to use influence score instead of transition probability to specify the active node from the social network. Here the application on expert identification in social influence graphs, We substitute the PageRank transition probability with the influence score. We consider the influence score as we define instead of traditional PageRank algorithm [17], in which $p(v|v')$ is simply the number of out links of node $p(v')$.

$$r[v] = \beta \frac{1}{|v|} + (1 - \beta) \sum_{v' : v' \longrightarrow v} r[v'] p(v|v') \tag{24}$$

$$p(v|v') = \frac{\sum_d \mu_{v'v}^d}{\sum_{v' : v' \longrightarrow v} \sum_d \mu_{v'v}^d} \tag{25}$$

$p(v|v')$ influence of node

Algorithm 6 *NIC* based predicting stars finding *(NICPS)*

Input: authors influence score, Author data
sqrt **Output:** Authors stars finding
Step 1: Work out author influence score by means of algorithm 4
Step 2: Stars identify by using Eq. 24

3.2.4 | Specific Topic Domain based Predicting Stars *(STDPS)*

In algorithm 6, defined the co-author relationship between other authors with the same domain to compute the author ranking.

$$r[v,d] = \beta \frac{1}{|v|} p(d_k|v) + (1-\beta) \sum_{v':v' \longrightarrow v} r[v',d] p(v|v',d) \tag{26}$$

$$p(v|v',d) = \frac{\mu^d_{v'v}}{\sum_{v_j{}':v' \longrightarrow v_j} \mu^d_{v'v_j}} \tag{27}$$

$p(v|v',d)$ epitomize the influence of one node v' to other node v on specific domain d; $p(d|v)$ is domain d based probability. The each node v, a vector of ranking scores $r[v;d]$, in which each node is specific to topic d while we select the co-author relationship randomly within same topic domain to define the topic based ranking score as: Topic model; $p(v|v',d)$ represents the probability of node $(v^{'})$ influencing node v on topic d where $p(d|v)$ is the probability of topic d generated by node v.

Algorithm 7 Specific topic domain based predicting stars finding *(STDPS)*

Input: Authors influence score
Output: Authors expert finding
Step 1: Work out author influence score by means of algorithm 4
Step 2: Using Eq. 26, stars finding with respect of specific topic domain

4 | EXPERIMENTS

To validate our proposed algorithm we extensively described the classification performance and the evaluation of predicting rising stars.

4.1 | Data sets

We used three real-world networks in our experiments, signifying Arnetminer, digital bibliography, and library project *(DBLP)* CORA. Arnetminer contain *38432* publication data, *Citeseer* contains *3,542*, and emphCora 2,834 contain *5239* publications data[9,56,57,58]. In our experiment *14* topic domain Machine Learning, Data mining, Databases, Semantic web, Information Retrieval, Human-Computer Interaction, Artificial Intelligence, Web service, Neural Networks, Case-Based, Probabilistic Methods, Rule Learning, Genetic Algorithms, Reinforcement Learning Theory; furthermore, the publications data of journal and conference from *1995 to 2000* are used in our experiment.

We examined that the generated subgraph will be more precise in the target domain on the individual network if the value of T will be large. The total number of node and edges in author subdomain A, where $|N_A| + |E_A| \ll N$, time complexity will be less than $O|N^2|$; moreover, the running time mainly affects if the value of T increase in our algorithm besides, it will be more helpful of fair prediction of rising stars. Furthermore, we built one transferring knowledge of common author subdomain data-set from two cross networks and chosen authors from each domain that are extremely improved the classification precision in the target domain. In the mutual database, when we used the source domain in the target domain. The similarity is absolutely correlated in the accuracy of classification because, in a scientific publication of both author domain citations, co-authorship, and venue association make highly effective for transfer learning.

4.1.1 | Impact the Depth of s-Neighborhood Structure

Classification precision is increased if we select more subgraphs to be transferred thru the target networks[60],[59],[34],[61]. The proposed algorithm outperforms on the distinct number of k subgraphs, as well as the highest value of k subgraph found very complex in source network. We analyze the influence of depth s-neighborhood structure and classification accuracy for nodes. If the value of s is one then we only take the immediate neighbor node. The number of nodes can rapidly increase of s-neighborhood structures if we recursively move the adjacent of a nodeąŕs adjacent. We change the depth of s values from *1* to *10*, *1* to *20* to make s-neighborhood structures for distinct network and different subgraphs to find the mutual subgraph between source and target networks.

4.2 | Performance Evaluation of Predicted Rising Stars

In this area there is a small amount of work is done to predict the rising stars. Its important challenge is to mine the novel scholars who will be a star in forthcoming. The first time we are using transfer learning to predict the target domain classification to predict and differentiate the difference between the rising stars, well established, stable and declining authors that revealed in Figure. 1 2.

4.2.1 | Rising Stars

Rising stars are said to be those persons/researchers who have currently low profile or who may not be in the top in their respective areas but they can be a star in the future. It is a kind of prediction in which a new person/research who is new to their respective field and can be a star in the future upon his features. Features are basically the impact of different factors on the new author which makes him/her a rising star e.g. if an author is working under the supervision of already experienced and have high profile authors have a high impact on new authors to become a predicting star. Predicting rising stars is one of the important and useful in different fields as if we appoint a young faculty member. This technique plays a vital role to appoint a rising star which will be definitely beneficial for the department or selecting reviewers for the journal, shown in Figure. 3.

4.2.2 | Author identifications analysis

In this section, we identified and differentiated the difference between the rising stars, well established, stable and declining stars. We have calculated authors score and authors influenced score that highly influenced the rank of final author scores.

We recognized those authors they were not predicting rising stars[1,17,8]. According to the above definition in Fig. 3, they are already well established, stable and declining authors whom we will not consider in predicting rising stars, as well as they; declared predicting stars in the previous methods[1,17,8]. Furthermore, consider only those authors who will be in the span of 1995 to 2000.

4.2.3 | Baseline Method evolution

The PubRank[17] predicted a *10* rising stars from database domain, StarRank[1] predicted *10* rising stars, and author[8] predicted *30* predicting rising stars shown in Table. 2 3 4. We have individually analyzed each author score sequentially with specific domain based on influence score, and mine *30* authors. Proposed algorithm give fair authors rank to respective authors and identified the rising stars, well established, stable, and declining authors which is ascertained of our algorithm, shown in Table. 2 3 4, despite the fact that more detail in Example. 1.

Mahmut T. Kandemir is declining author, he published 2004 (1, 53), 2005(1, 10), 2006(2, 62)čň2014 (10, 65), 2015(11, 55)čň2016 (14, 45) research article. The author has 1 publication in 2004 and got 53 citation, in 2005 have

TABLE 2 Performance comparison of Predicting rising stars using 1st data-set

	Author Name	PubRank[17]	StarRank[1]	[8]	Proposed	AS
1	Moses Charikar	NA	NA	Rising Star	Rising Star	1.59
2	Ravi Kumar	NA	NA	Rising Star	Rising Star	1.81
3	Rajeev Alur	NA	NA	Rising Star	Well Established	2.21
4	B.F. F.Ouellette	NA	NA	Rising Star	Well Established	1.05
5	Amit Sahai	NA	NA	Rising Star	Rising Star	1.54
6	Ee-Peng Lim	NA	NA	Rising Star	Well Established	1.12
7	S. Rajagopalan	NA	NA	Rising Star	Well Established	1.22
8	Hari Balakrishnan	NA	NA	Rising Star	Well Established	2.64
9	Sudipto Guha	NA	NA	Rising Star	Well Established	1.32
10	Sonia Fahmy	NA	NA	Rising Star	Well Established	0.48
11	Mahmut T. Kandemir	NA	NA	Rising Star	Declining Author	0.08
12	Barbara A. Rapp	NA	NA	Rising Star	Well Established	0.73
13	Byron Dom	NA	NA	Rising Star	Well Established	1.09
14	V. Guruswami	NA	NA	Rising Star	Rising Star	1.08
15	S. Chakrabarti	NA	NA	Rising Star	Well Established	1.28
16	Chandra Chekuri	NA	NA	Rising Star	Rising Star	1.13
17	David L. Wheeler	NA	NA	Rising Star	Well Established	2.44
18	S. Kalyanaraman	NA	NA	Rising Star	Well Established	0.92
19	Ian Horrocks	NA	NA	Rising Star	Rising Star	1.88
20	Rajeev Rastogi	Rising Star	NA	Rising Star	Well Established	1.47
21	Thad Starner	NA	NA	Rising Star	Well Established	1.29
22	Wee Keong Ng	NA	NA	Rising Star	Stable	0.19
23	David J. Lipman	NA	NA	Rising Star	Well Established	2.58
24	Michael A. Bender	NA	NA	Rising Star	Well Established	0.35
25	Srinivasan Seshan	NA	NA	Rising Star	Well Established	1.30
26	Jeen Broekstra	NA	NA	Rising Star	Declining Author	0.41
27	George Karypis	NA	NA	Rising Star	Well Established	0.52
28	Gonzalo Navarro	NA	NA	Rising Star	Rising Star	1.06
29	Steven D. Gribble	NA	NA	Rising Star	Well Established	1.24
30	Erik D. Demaine	NA	Rising Star	Rising Star	Rising Star	1.13
31	Wei Ying Ma	NA	Rising Star	NA	Rising Star	1.69
32	Philip S. yu	Rising Star	Rising Star	NA	Well Established	2.44
33	Jiawei Han	Rising Star	Rising Star	NA	Well Established	2.60
34	Zheng Chen	NA	Rising Star	NA	Well Established	0.85
35	Divesh Srivastava	NA	Rising Star	NA	Well Established	1.19
36	Wei Wang	NA	Rising Star	NA	Well Established	1.20
37	Hsinchun Chen	NA	Rising Star	NA	Well Established	1.27
38	Bertram Ludscher	NA	Rising Star	NA	Well Established	0.39
39	Lee Tan	NA	Rising Star	NA	Declining Author	0.01
40	B. K. Bhargava	Rising Star	NA	NA	Stable	0.12
41	H. V. Jagadish	Rising Star	NA	NA	Well Established	1.18
42	Hamid Pirahesh	Rising Star	NA	NA	Well Established	1.03
43	Ming-Syan Chen	Rising Star	NA	NA	Well Established	1.24
44	Rakesh Agrawal	Rising Star	NA	NA	Well Established	1.01
45	Richard R. Muntz	Rising Star	NA	NA	Well Established	1.09
46	Shi-Kuo Chang	Rising Star	NA	NA	Well Established	10.35

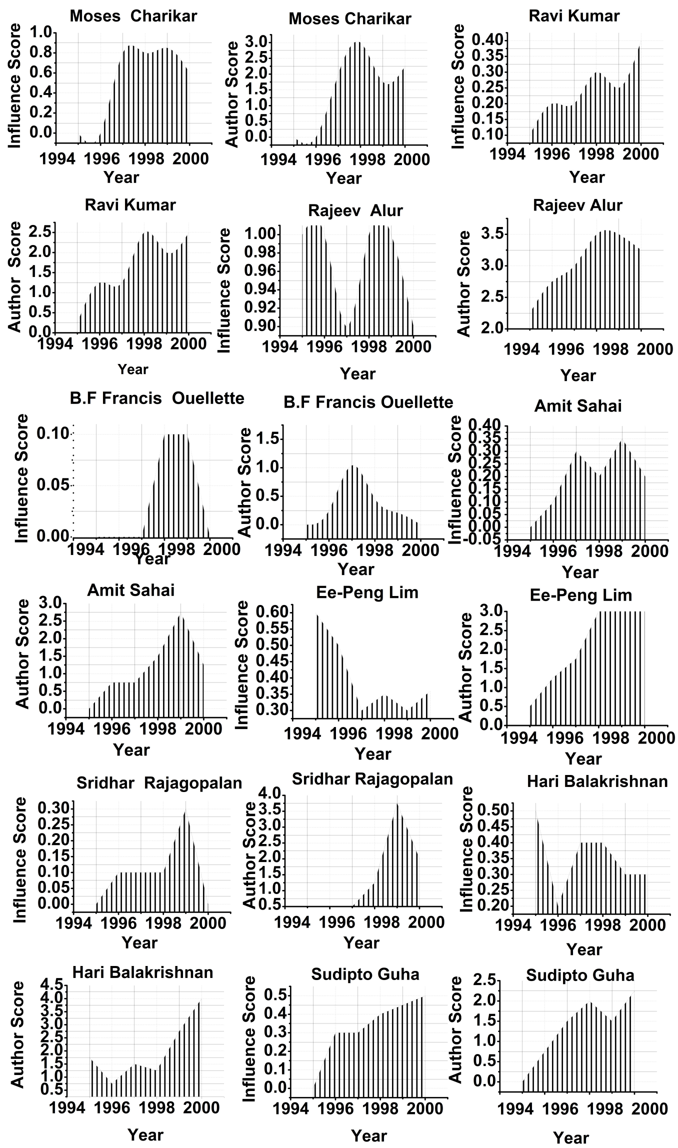

FIGURE 1 Performance evaluation of rising stars, well established, stable and declining authors(First Data set)

1 publication and got 10 citations, in 2006 have 2 publications and got 62 citations even though have no publication between 1995 to 2000, he had declared predicting star in the previous method. The author **Rakesh Agrawal** is a well-established author. He published a research article in 1965(1,0), 1970(3.0), 1979(2,3), 1980(8,0), 1981(3,0), 1982(1,0)čň1983(6,97), 1984(4,1), 1985(12,739), 1986(4,0), 1987(12,964), 1988(7,450), 1989(14,1010), 1990(11,329), 1991(22,574), 1992(10,352), 1993(28,22327), 1994(14, 22853). He has 1 publication and 0 citations in 1965, 3 research publications and 0 citations in 1970, and so on. **Jiawei Han** is a well-established author. He published in 1985(2, 14), 1986(1, 41), 1987(1, 37), 1988(6,107), 1989(4, 63), 1990(4, 96), 19991(9,368), 1992(9,709), 1993(14,302), 1994(18, 5640) research article. He has 2 publications and 14 citations in 1985, in 1978 has 1 publication and 37 citations, and so on.

Philip S. yu is a well-established author. He published in 1977(3,28), 1978(1, 0)čň1981(1, 10), 1983(2, 7), 1985(3, 120), 1986(7, 120), 1987(7, 665), 1988(7, 72), 1989(14, 1010),1990(13, 626), 1991(14, 985), 1992(24, 999), 1993(18, 1209), 1994(22, 770). He has 3 publications in 1977 and got 28 citations, 1 research article and got 0 citations in 1978, and so on. **Jianbo Shi** is a well-established author. He has published in 1993 (2, 8273), 1994(1, 0). He has 2 publication in 1993 and got 8273 citations and so on. **David J. Lipman** is a well-established author. He has published

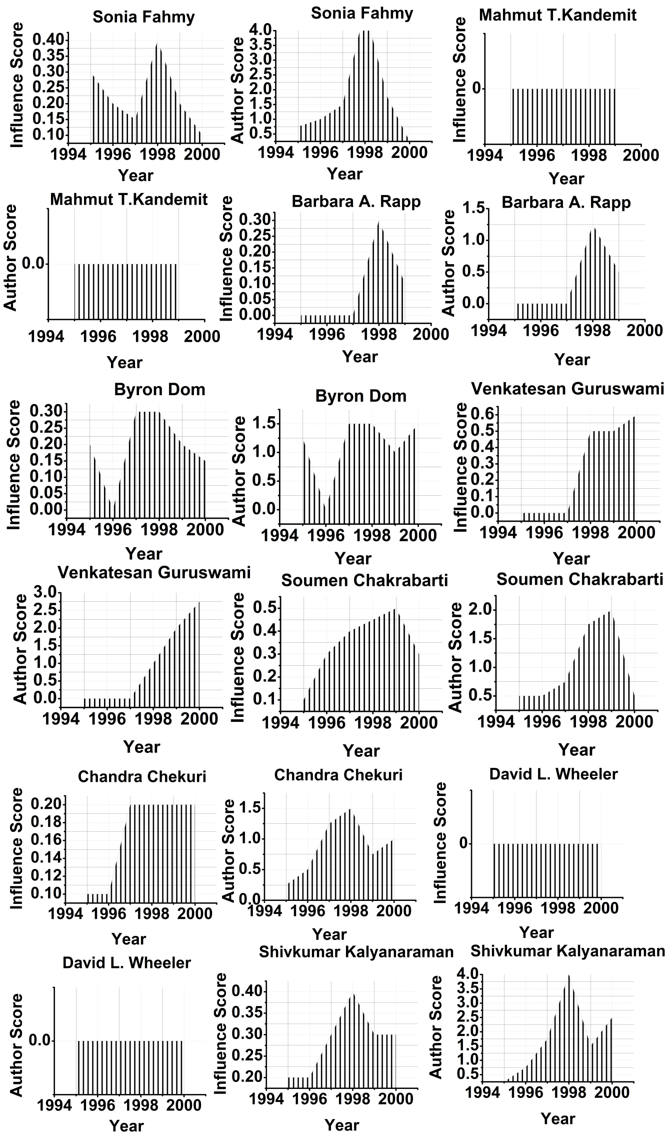

FIGURE 2 Performance evaluation of rising stars, well established, stable and declining authors(Second Data set)

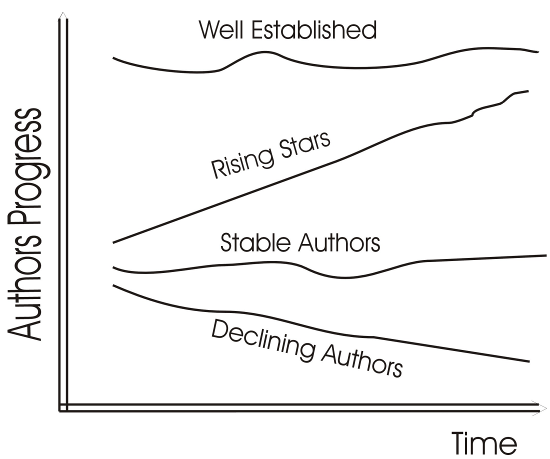

FIGURE 3 Predicting rising star definition, author evolution Tsatsaronis et al[62]

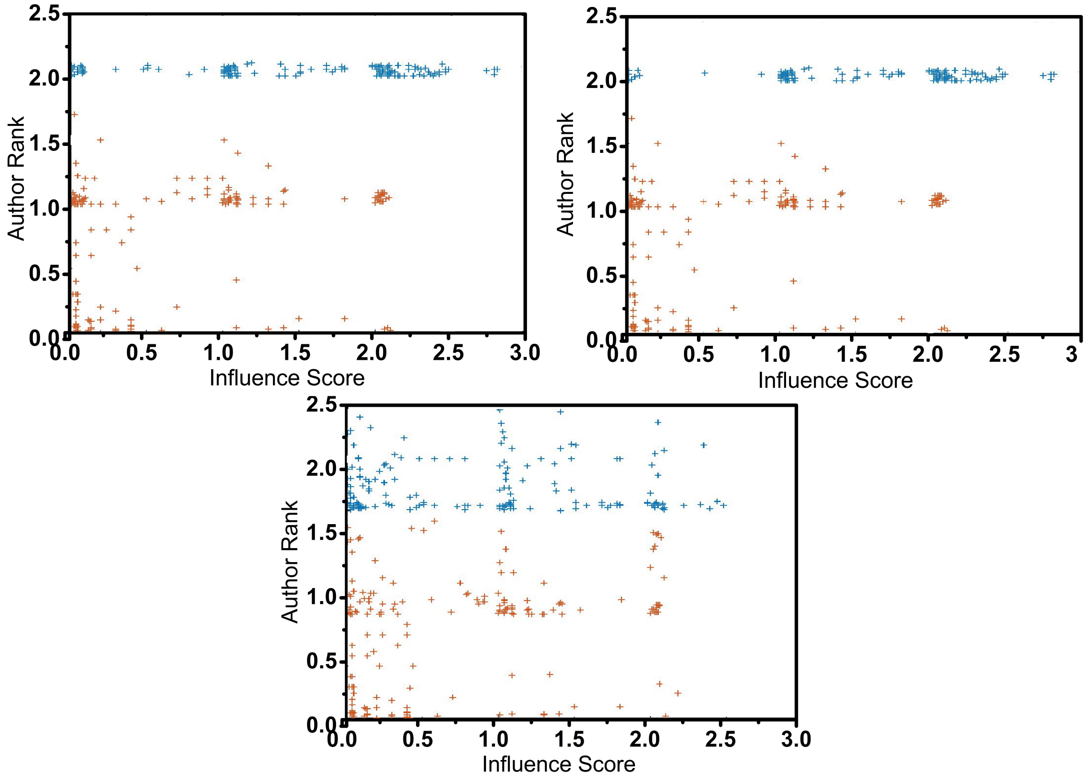

FIGURE 4 Predicting upcoming rising stars

in 1979(1, 0), 1982(2, 6), 1983(1, 0)čň1984(2, 116), 1985(1, 12), 1987(1, 12), 1988(1, 12743), 1989(2, 428), 1990 (5, 69600) 1991(2, 1130), 1993(2, 4428). He has 1 publication in 1983 and got 0 citations, in 1984 he published 2 research articles and got 116 citations, and so on. **Michel C. A. Klein** is declining author, he published 2000 (3, 135) research article. The author has 3 publication in 2004 and got 135 citations and have no any more research article in the span of 1995 to 2000. **Evgeni M. Zdobnov** is declining author, he published 2000 (3, 579) research article. The author has 3 publication in 2004 and got 579 citations and have no any more research article in the span of 1995 to 2000.

4.3 | Result and discussion

We revealed the efficiency of proposed techniques *CAMIPS*, *STDPS*, *NICPS* and nodes characteristics for identification on co-authors and citations data set. The previous method selected the representative nodes because of high citation numbers. Proposed algorithms identify the influence between papers; consequently, it can differentiate the citations of academic background of a paper and odd citations. The influenced representative researchers, as well as some influence representative papers, are shown in Table. 5 6. Preceding methods used to estimate the similar influence score according to similarity-based cosine metric to analyze the social influence of online communities[54]. Our method has many different advantages over the similarity-based method. Previous methods can only calculate the similarity between the nodes but cannot provide any information or data regarding the influence of node on each other.

Using the list of top-30 authors are presented in descending order while all authors have an excellent google scholar profile having a high citation of each paper, besides impressive publication groups like ACM, IEEE, AAAS, and NSERCC SIAM. Furthermore, they also have achieved in different top-level forums like IBM Outstanding Technical Achievement Awards, IBM Canada Research Impact of the Year Award, IBM Outstanding Innovation Award, and IBM Outstanding Innovation Award. They are experts and predicted rising stars during the period of 1995 – 2000. If some of them have not become an expert from our top-30 list but still they are rising stars by our method for the reason that there may be several different causes to not continue his research like starting university career, work

TABLE 3 Performance comparison of Predicting rising stars using second data-set

	Author Name	PubRank[17]	StarRank[1]	[8]	Proposed	AS
1	Vahid Tarokh	NA	NA	Rising Star	Well Established	0.31
2	Ewan Birney	NA	NA	Rising Star	Well Established	0.26
3	B.A. R.Neto	NA	NA	Rising Star	Rising Star	0.25
4	Thorsten Joachims	NA	NA	Rising Star	Well Established	0.34
5	Jianbo Shi	NA	NA	Rising Star	Well Established	0.27
6	Hamid Jafarkhani	NA	NA	Rising Star	Well Established	0.21
7	Hari Balakrishnan	NA	NA	Rising Star	Well Established	0.41
8	E.L.L.Sonnhammer	NA	NA	Rising Star	Well Established	0.31
9	B. F. F. Ouellette	NA	NA	Rising Star	Well Established	0.15
10	Ian Horrocks	NA	NA	Rising Star	Rising Star	0.30
11	Dieter Fox	NA	NA	Rising Star	Well Established	0.29
12	Nello Cristianini	NA	NA	Rising Star	Well Established	0.27
13	S.Rajagopalan	NA	NA	Rising Star	Well Established	0.18
14	Steve Lawrence	NA	NA	Rising Star	Well Established	0.19
15	Chris Stauffer	NA	NA	Rising Star	Rising Star	0.16
16	Mark Handley	NA	NA	Rising Star	Well Established	0.26
17	Keith A. Crandall	NA	NA	Rising Star	Well Established	0.17
18	Ravi Kumar	NA	NA	Rising Star	Rising Star	0.22
19	Robert Cooley	NA	NA	Rising Star	Rising Star	0.13
20	Eckart Zitzler	NA	NA	Rising Star	Rising Star	0.18
21	Rajeev Rastogi	Rising Star	NA	Rising Star	Well Established	0.21
22	David J. Lipman	NA	NA	Rising Star	Well Established	0.32
23	P. J.Phillips	NA	NA	Rising Star	Well Established	0.20
24	George Karypis	NA	NA	Rising Star	Well Established	0.21
25	E.M.B-Royer	NA	NA	Rising Star	Declining Author	0.22
26	Iftach Nachman	NA	NA	Rising Star	Rising Star	0.14
27	Byron Dom	NA	NA	Rising Star	Well Established	0.17
28	Patrick J. Rauss	NA	NA	Rising Star	Rising Star	0.13
29	Hendrik Blockeel	NA	NA	Rising Star	Rising Star	0.15
30	Sudipto Guha	NA	NA	Rising Star	Well Established	0.26
31	Wei Ying Ma	NA	Rising Star	NA	Rising Star	0.34
32	Philip S. yu	Rising Star	Rising Star	NA	Well Established	0.61
33	Jiawei Han	Rising Star	Rising Star	NA	Well Established	0.75
34	Zheng Chen	NA	Rising Star	NA	Well Established	0.14
35	Divesh Srivastava	NA	Rising Star	NA	Well Established	0.27
36	Wei Wang	NA	Rising Star	NA	Well Established	0.26
37	Hsinchun Chen	NA	Rising Star	NA	Well Established	0.32
38	B.ludaumlscher	NA	Rising Star	NA	Well Established	0.17
39	Lee Tan	NA	Rising Star	NA	Declining Author	0.02
40	B.K.Bhargava	Rising Star	NA	NA	Stable	0.04
41	H. V. Jagadish	Rising Star	NA	NA	Well Established	0.33
42	Hamid Pirahesh	Rising Star	NA	NA	Well Established	0.18
43	Ming-Syan Chen	Rising Star	NA	NA	Well Established	0.24
44	Rakesh Agrawal	Rising Star	NA	NA	Well Established	0.20
45	Richard R. Muntz	Rising Star	NA	NA	Well Established	0.22
46	Shi-Kuo Chang	Rising Star	NA	NA	Well Established	0.05
47	Erik D. Demaine	NA	Rising Star	NA	Rising Star	0.20

TABLE 4 Performance comparison of Predicting rising stars using Database Domain

	Author Name	PubRank[17]	StarRank[1]	[8]	Proposed	AS
1	Ravi Kumar	NA	NA	Rising Star	Rising Star	1.89
2	Moses Charikar	NA	NA	Rising Star	Rising Star	1.79
3	B.A. Rapp	NA	NA	Rising Star	Well Established	0.85
4	D.L. Wheeler	NA	NA	Rising Star	Well Established	2.49
5	B.F.F.Ouellette	NA	NA	Rising Star	Well Established	0.80
6	Rohit Goyal	NA	NA	Rising Star	Stable	0.10
7	Sonia Fahmy	NA	NA	Rising Star	Well Established	0.51
8	Amit Sahai	NA	NA	Rising Star	Rising Star	1.61
9	V.Guruswami	NA	NA	Rising Star	Rising Star	1.12
10	Rajeev Alur	NA	NA	Rising Star	Well Established	2.28
11	S.Rajagopalan	NA	NA	Rising Star	Well Established	1.23
12	E. M. Zdobnov	NA	NA	Rising Star	Declining Author	0.13
13	S.Kalyanaraman	NA	NA	Rising Star	Well Established	0.99
14	Ian Horrocks	NA	NA	Rising Star	Rising Star	1.93
15	E.D. Demaine	NA	NA	Rising Star	Rising Star	1.20
16	M.T. Kandemir	NA	NA	Rising Star	Declining Author	0.09
17	Jeen Broekstra	NA	NA	Rising Star	Declining Author	0.50
18	Michael A. Bender	NA	NA	Rising Star	Well Established	0.41
19	S.Chakrabarti	NA	NA	Rising Star	Well Established	1.33
20	Srinivasan Seshan	NA	NA	Rising Star	Well Established	1.38
21	Chandra Chekuri	NA	NA	Rising Star	Rising Star	1.15
22	Byron Dom	NA	NA	Rising Star	Well Established	0.22
23	M.C. A. Klein	NA	NA	Rising Star	Declining Author	0.05
24	Ayman F. Naguib	NA	NA	Rising Star	Declining Author	0.03
25	Wee Keong Ng	NA	NA	Rising Star	Stable	0.24
26	David J. Lipman	NA	NA	Rising Star	Well Established	2.61
27	Bettina Kemme	NA	NA	Rising Star	Declining Author	0.53
28	Fulvio Corno	NA	NA	Rising Star	Stable	0.34
29	Stephan Tobies	NA	NA	Rising Star	Stable	0.45
30	Hari Balakrishnan	NA	NA	Rising Star	Well Established	2.57
31	Wei Ying Ma	NA	Rising Star	NA	Rising Star	1.73
32	Philip S. yu	Rising Star	Rising Star	NA	Well Established	2.39
33	Jiawei Han	Rising Star	Rising Star	NA	Well Established	2.65
34	Zheng Chen	NA	Rising Star	NA	Well Established	0.94
35	Divesh Srivastava	NA	Rising Star	NA	Well Established	1.25
36	Wei Wang	NA	Rising Star	NA	Well Established	1.24
37	Hsinchun Chen	NA	Rising Star	NA	Well Established	1.31
38	B.ludaumlscher	NA	Rising Star	NA	Well Established	0.42
39	Lee Tan	NA	Rising Star	NA	Declining Author	0.01
40	B.K.Bhargava	Rising Star	NA	NA	Stable	0.13
41	H. V. Jagadish	Rising Star	NA	NA	Well Established	1.19
42	Hamid Pirahesh	Rising Star	NA	NA	Well Established	1.09
43	Ming-Syan Chen	Rising Star	NA	NA	Well Established	1.27
44	Rakesh Agrawal	Rising Star	NA	NA	Well Established	1.08
45	Richard R. Muntz	Rising Star	NA	NA	Well Established	1.12
46	Shi-Kuo Chang	Rising Star	NA	NA	Well Established	0.39
47	Rajeev Rastogi	Rising Star	NA	NA	Well Established	1.49
48	Erik D. Demaine	NA	Rising Star	NA	Rising Star	1.16

TABLE 5 Nodes discovering

Dataset	Topics	Nodes
Authors	Machine Learning	Vasant Honavar, Thomas G. Dietterich, Tom M. Mitchell, Pat Langley, Luc De Raedt, Zhihua Zhou, Raymond J. Mooney, Ryszard S. Michalski
–	Data mining	jiawei Han, Philip s.yu, Rakesh Agrawal, John C. Shafer, Qiang Yang, Bing Liu, Christos Faloutsos, Jian Pei, Charu C. Aggarwal, Vipin Kumar, Xindong Wu, Wei Wang
–	Database System	David J. DeWitt, Michael J. Carey, jiawei Han, Shamkant B. Navathe, Michael Stonebraker, Philip s.yu, Jennifer Widom, Jeffrey D. Ullman,
–	Semantic Web	Steffen Staab, James Hendler, Amit P. Sheth, Tim Finin, Dieter Fensel, Frank Van Harmelen Deborah L. Mcguinness, Rudi Studer, Andrew Tomkins, Tim Berners-Lee
–	Information Retrieval	W. Bruce Croft, Gerard Salton, Susan T. Dumais, Justin Zobel, James Allan, Nicholas J. Belkin Alan F. Smeaton, James P. Callan, Maarten De Rijke
–	Web Service	Boualem Benatallah, Sheila Mcilraith, Fabio Casati, Carole Goble Geoffrey C. Fox, Schahram Dustdar
Citation	Machine Learning	Ensemble methods in machine learning Combining labeled and unlabeled data with co-training
–	Data mining	Fast algorithms for mining association rules Mining association rules between sets of items in large databases
–	Database System	The Object-Oriented Database System Manifesto Data Mining: An Overview from a Database Perspective
–	Semantic Web	The Semantic Web, OWL Web Ontology Language Overview Knowledge engineering: principles and methods
–	Information Retrieval	Introduction to Modern Information Retrieval,Information retrieval Indexing by latent semantics analysis

TABLE 6 Evaluation of co-authors network influence analysis of one node (Co- SA is Co-Stable Authors, Co- RA is Co- Declining Authors

Topic: Data Mining	Topic: Database	Topic: Machine Learning
Jiawei Hen : Heikki Mannila	**Jiawei Hen :Heikki Mannila**	**Jiawei Hen : Heikki Mannila**
David Clutter : Arianna Gallo	David Clutter : Heikki Lokki	David Clutter : Heikki Lokki
Hasan M. Jamil : Heikki Lokki	Chinying Chaou :Vesa Ollikainen	Hasan M. Jamil: Vesa Ollikainen
Larry Travis : Paivi Onkamo	Hasan M. Jamil : Arianna Gallo	Chinying Chaou :Marko Salmenkivi
Wo-Shun Luk : Vesa Ollikainen	Wo-Shun Luk :Marko Salmenkivi	Wo-Shun Luk :Arianna Gallo
Chinying Chaou : Marko Salmenkivi	Larry Travis :Paivi Onkamo	Larry Travis :Paivi Onkamo

with a different professor for his Ph.D. or start working in top research labs. For instance, if you have started with your teaching career which has an almost high workload and less time for research so definitely you didn't find the same motivation or environment to do the research. Below in Table. 7 we declared *30* predicting rising stars(Using citation-based, Paper-based, Author influence based, Specific topic influence based). The best of our information is

TABLE 7 Predicting rising stars (AS represent Authors score)

	Authors Name	Influence Score	AS
1	Wei Ying Ma	Assistant Managing, Director Microsoft Research Asia	2.21
2	Steffen Staab	Professor Faculty of Computer Science of the University of Koblenz Landau	2.20
3	Ravi kumar	Senior Staff Research Scientist Google	2.18
4	Jian Pei	Professor, School of Computing Science, Simon Fraser University	2.17
5	Ian Horrocks	Professor, Department of Computer Science, Oxford University	2.15
6	P.Jonathon Phillips	The National Institute of Standards and Technology, USA	2.14
7	Amit Sahai	Professor, Department of Computer Science, UCLA, Los Angeles	2.12
8	Boualem Benatallah	Professor, School of Computer Science and Engineering, New South Wales	2.11
9	Berthier Ribeiro Neto	Associate Professor, Dept. of CS Federal University of Minas, Gerais	2.10
10	Moses Charikar	Professor, Department of Computer Science, Princeton University	2.09
11	Ling Liu	Professor, College of Computing, Georgia Institute of Technology	2.07
12	Erik D Demanine	Professor, MIT Computer Science and Artificial Intelligence Laboratory, USA	2.06
13	Roger Wattenhofer	Professor, Information Technology and Electrical Engineering,Switzerland	2.03
14	David Blaauw	Professor, Dept. of Computer Engineering University of Michigan, Ann Arbor, MI	1.98
15	Wei Wang	Professor, Intelligence Control Research Institute,China	1.95
16	venkatesan Guruswami	Professor, Department of Computer Science, Carnegie Mellon University	1.93
17	Jian Zhang	Researcher, Institute of Genetics and Developmental Biology, CAS	1.92
18	Marlon Dumas	Professor, University of Tartu	1.90
19	Dennis Sylvester	University of Michigan, Ann Arbor, MI	1.87
20	James T. Kwok	Professor, Dept. of CS, The Hong Kong University of Science and Technology	1.86
21	Lawrence T. Pileggi	Carnegie Mellon University, Pittsburgh, PA	1.83
22	Chandra Chekuri	Professor, Department of Computer Science, University of Illinois	1.81
23	Rupak Majumdar	Professor, Department of Computer Science, University of California	1.77
24	Igor L. Markov	Professor, University of Michigan	1.72
25	Wagner Meira Jr	Professor, Universidade Federal de Minas Gerais	1.71
26	Xin Li	National Outstanding Youth winner Cold and Arid Regions Environmental, China	1.24
27	Stephen G. Kobourov	Professor, Department of CS , University of Arizona	1.69
28	Orit Hazzan	Professor, Department of Education in Science, Israel Institute of Technology	1.24
29	Moshe Lewenstein	Bar Ilan University	1.68
30	Masayuki Takeda	Professor, Department of Informatics, Kyushu University	1.65

TABLE 8 Evaluation of co-authors network influence analysis of one node (Co- SA is Co-Stable Authors, Co- RA is Co- Declining Authors

Node	Co-Well Established Node	Co-SA Node	Co-DA Node	Co-RA Node
David J. Lipman	John J. Rossi	Barbara A. Rapp	Jacob Maizel	
	Temple F. Smith	Zheng Zhang	Michael Swatemant	
	W. John Wilbur		B. Lee	
	Michael S. Waterman		Eugene W. Myers	
	Richard W. Pastor		Dennis Benson	
	William R. Pearson		Mark Boguski	
	Stephen F. Altschul		D. A. Benson	
	Raymond J. Carroll		Karen Clark	
	Warren Gish		Wilma Ross	
	Webb Miller		Arthur Landy	
	James Ostell		A. A. Schaffer	
	Ilene Karsch-Mizrachi		Jinghui Zhang	
	Gregory D. Schuler			
	Eric W. Sayers			
	Alejandro A. Sch?ffer			
	Thomas L. Madden			
	Eugene V. Koonin			
	Roman L. Tatusov			
	J. Zhang			
	B. F. Francis Ouellette			
	David L. Wheeler			

our first exertion to persuade transfer learning knowledge across different networks to predict and identify the rising stars, well established, stable, declining stars, and influence topic discovery in academic social networks.

In this section, we evaluate the efficiency of *ACTL* and outcome of expert finding exposed in Table 5, 6, 7, 8. We perceived that the topic-based social influences, node-based social influences approach can improve the accuracy of expert finding which approved the effectiveness of the *ACTL* method for topic-base influence analysis and node-based social influences e. g (David J. Lipman is not predicting rising stars, as well as David J. Lipman, proclaimed predicting rising stars in the previous method. David J. Lipman is well established authors according to definition Tsatsaronis et al.[62], further node-based social influences approach *NICPS* discovered *21* co-well established nodes, *2* co-stable, *12* co- declining nodes and *0* predicting stars between the time span from *1995* to *2000* shown in Table 8.

We declared predicting rising star between the *0.5* to *1.5* threshold values, shown in Figure. 4 and predicting star accuracy with existing methods. Even though for expert search the different classification algorithms, information retrieval, and graph clustering work were already done[16,13,63,64,65,66]; however, the aim of this study is to predict upcoming rising stars by means of transfer learning in the area of two or more co-author networks. As far as our knowledge is concerned, no previous work has been done regarding the measuring of topic-level and node-level social influence on large-scale networks classification based on transfer learning and predicting upcoming rising stars.

5 | CONCLUSIONS

In this area there is a small amount of work is done to predict the rising stars. Its important challenge is to mine the novel scholars that will be a star in the future. We have persuaded a novel approach, Author Classification algorithm using Transfer Learning *(ACTL)* to learn new tasks on target area to mine external knowledge from the source domain. As far as our knowledge is concerned, no previous work has been done regarding the topic-level and node-level social influence on large-scale networks to classify using transfer learning to predict and differentiate the well-established, stable and declining authors. The main idea if a junior researcher works with expert researchers having a chance to be experts in the future. In node-weighting schemes, we have designed a node weighting techniques to compute mutual influence scores in specific topic domain, corresponding author mutual influence, co-authorąŕs citations based mutual influence, co-authorąŕs venues based mutual influence, and co-authorąŕs paper-based mutual influence schemes with respect to fair contribution. In predicting rising stars schemes, we have calculated Corresponding Author Mutual Influence based on Predicting Stars *(CAMIPS)*, Node-based Influence score Predicting Stars finding*(NICPS)*, and Specific Topic Domain-based Predicting Stars to detect well-established, stable, declining authors, predicting star *(STDPS)*, and topic-based node discovering. We observed that proposed methods highly improved the accuracy of future rising star prediction and achieved superior performances compared with other state-of-art techniques.

Acknowledgement

This work is partially supported by the National High Technology Research and Development program of China (863 program) under Grant 2014AA012204, the NSFC under Grant 61671018. , Chinese Government Scholarship (CSC),

Competing interests

The authors declare that they have no competing interests.

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